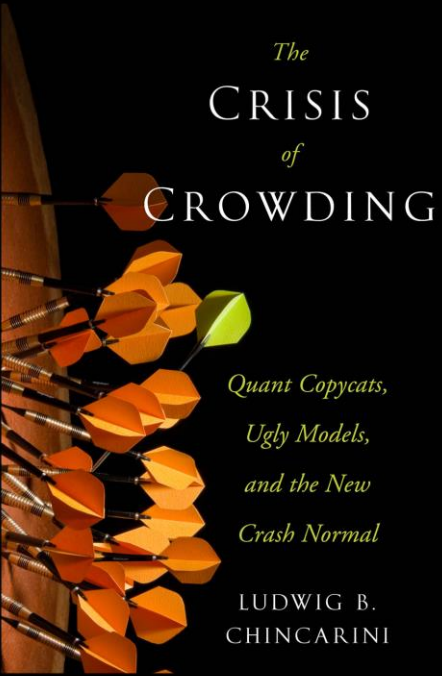
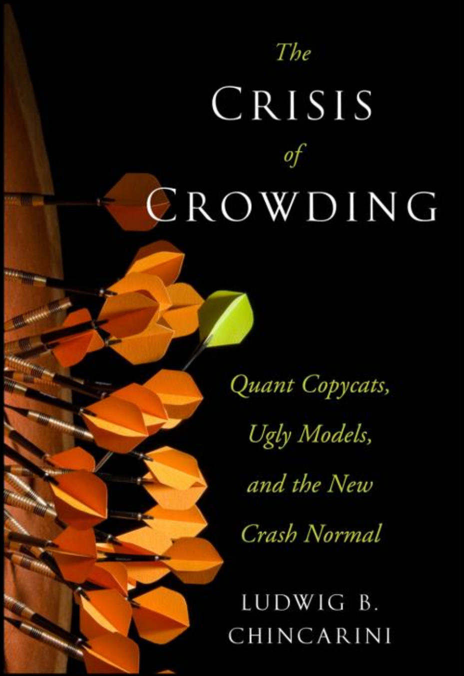


New Observations on Crowding & Selectivity Theory



October 13, 2020

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United States Commodity Fund Investments

UNIVERSITY OF SAN FRANCISCO | School of Management

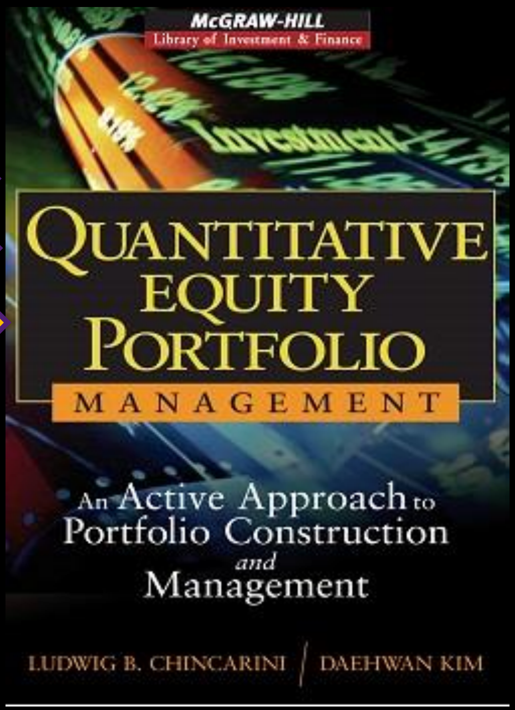
BERNSTEIN'S 17TH ANNUAL QUANTITATIVE FINANCE CONFERENCE

Zoom virtual conference

WEDGE Capital Management®

- Thank you Ann Larson and Sanford Bernstein.

New Edition of QEPM will be released in 2021. Please look out for it. ;)



1. Crowding Idea is Spreading

- *The Crisis of Crowding* by Ludwig Chincarini.

- A new academic literature on crowding has been burgeoning in the last seven years.

- Practitioner research has also exploded and been very dedicated to crowding research.

- For more info, go to: http://ludwigbc.com/presentations/slides/

(Lots of stuff, including latest research, definitions, etc)

2. New Observations on Crowding

Most of the new observations are contained in Appendix A to this presentation which has summaries of the latest articles on crowding.

You can get a copy of this presentation from me directly (chincarinil@hotmail.com) or from Sanford Bernstein.

2. New Observations on Crowding

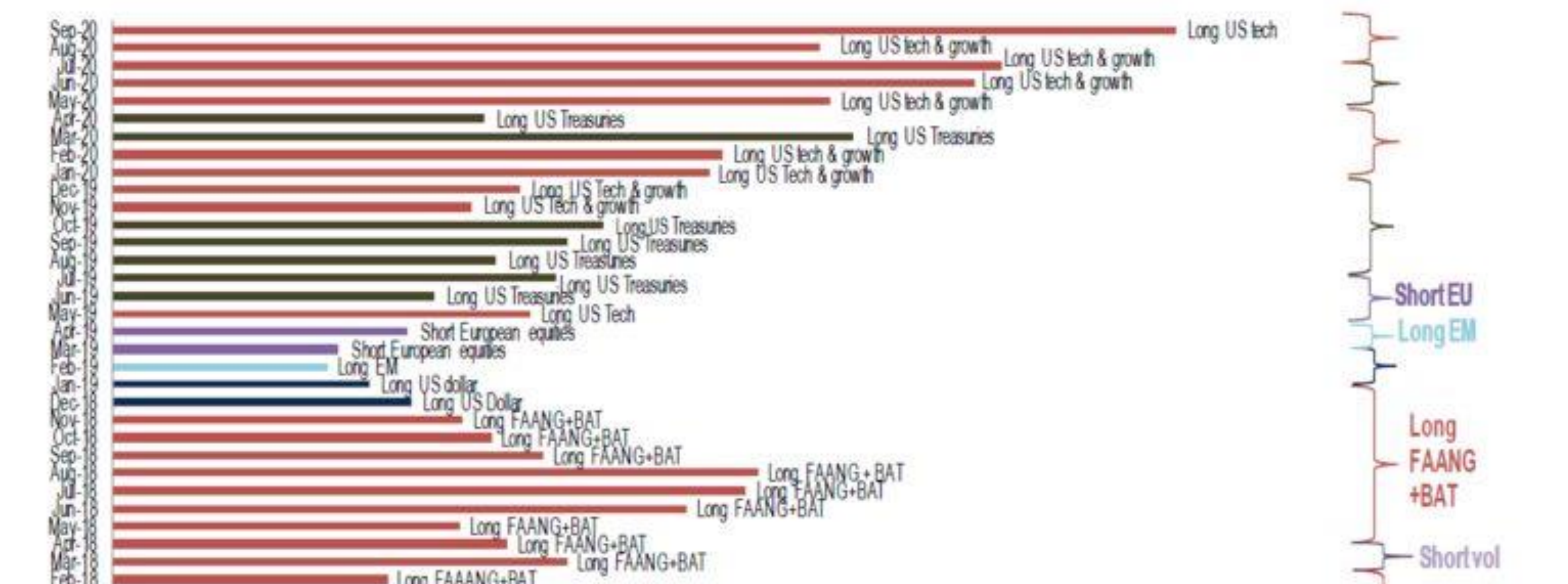
Active Managers Had Worst Stumble in Two Years Last Month

By Lu Wang
August 10, 2020, 10:32 AM PDT

- It's a turnaround from the first half, when beat ratio hit 48%
- Concentration 'increasingly problematic' for funds, BofA says

2. New Observations on Crowding
September 2020 – LONG US TECH

Exhibit 16: Evolution of Global FMS "most crowded trade"



More than half of those surveyed said long U.S. technology/growth stocks is the most crowded trade (51%), followed by long U.S. Treasuries (17%) and long investment-grade corporate bonds (13%).

2. New Observations on Crowding

Sanford Bernstein Crowding Research (09/24/2020)

Biggest, Most Crowded Tech Stocks in USA

Bloomberg Ticker	Company	Market Cap (USD Bil)	Long-Term Performance	Percentage Sell-Side Analyst Buy Ratings	Aggressive Estimates with Implied Achievability	Adjusted Overweights by Active Managers	Institutional Trade Persistence	Current Overall Crowding Decile
AAPL US	APPLE	1876	1	5	3	1	5	1
MSFT US	MICROSOFT CO	1541	1	2	3	1	8	1
V US	VISA A	330	2	2	5	1	8	1
MA US	MASTERCARD A	326	2	3	4	1	5	1
NVDA US	NVIDIA	304	1	4	2	1	5	1
ADBE US	ADOBE	225	1	4	4	1	5	1
PYPL US	PAYPAL HOLDINGS	214	1	2	2	1	5	1
CRM US	SALESFORCE.COM	214	2	2	5	1	7	1
ACN US	ACCENTURE A	137	2	4	4	1	7	1
QCOM US	QUALCOMM	126	1	5	2	1	8	1

2. New Observations on Crowding

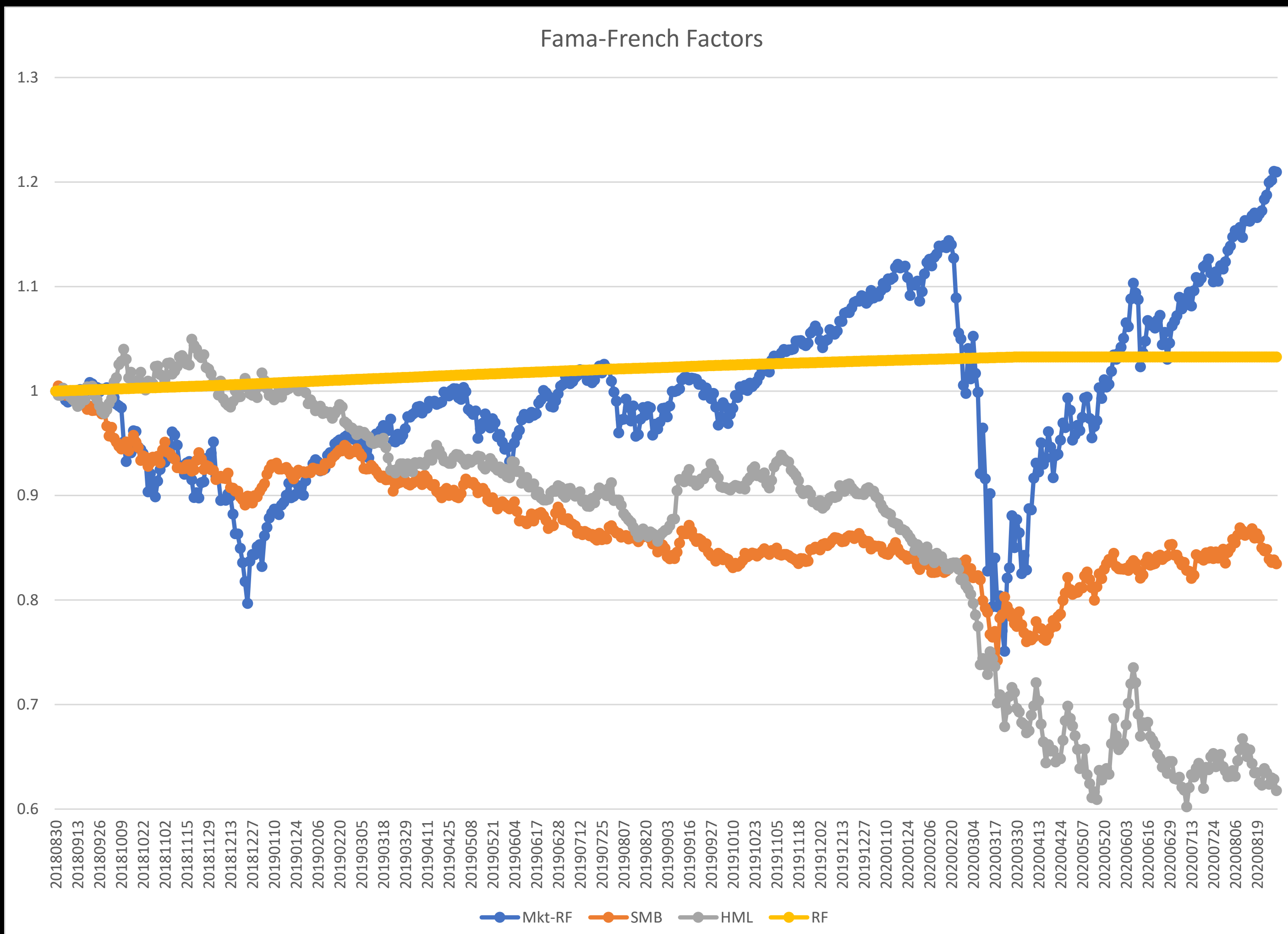
Sanford Bernstein Crowding Research (09/24/2020)

Biggest, Most Crowded Tech Stocks in Europe

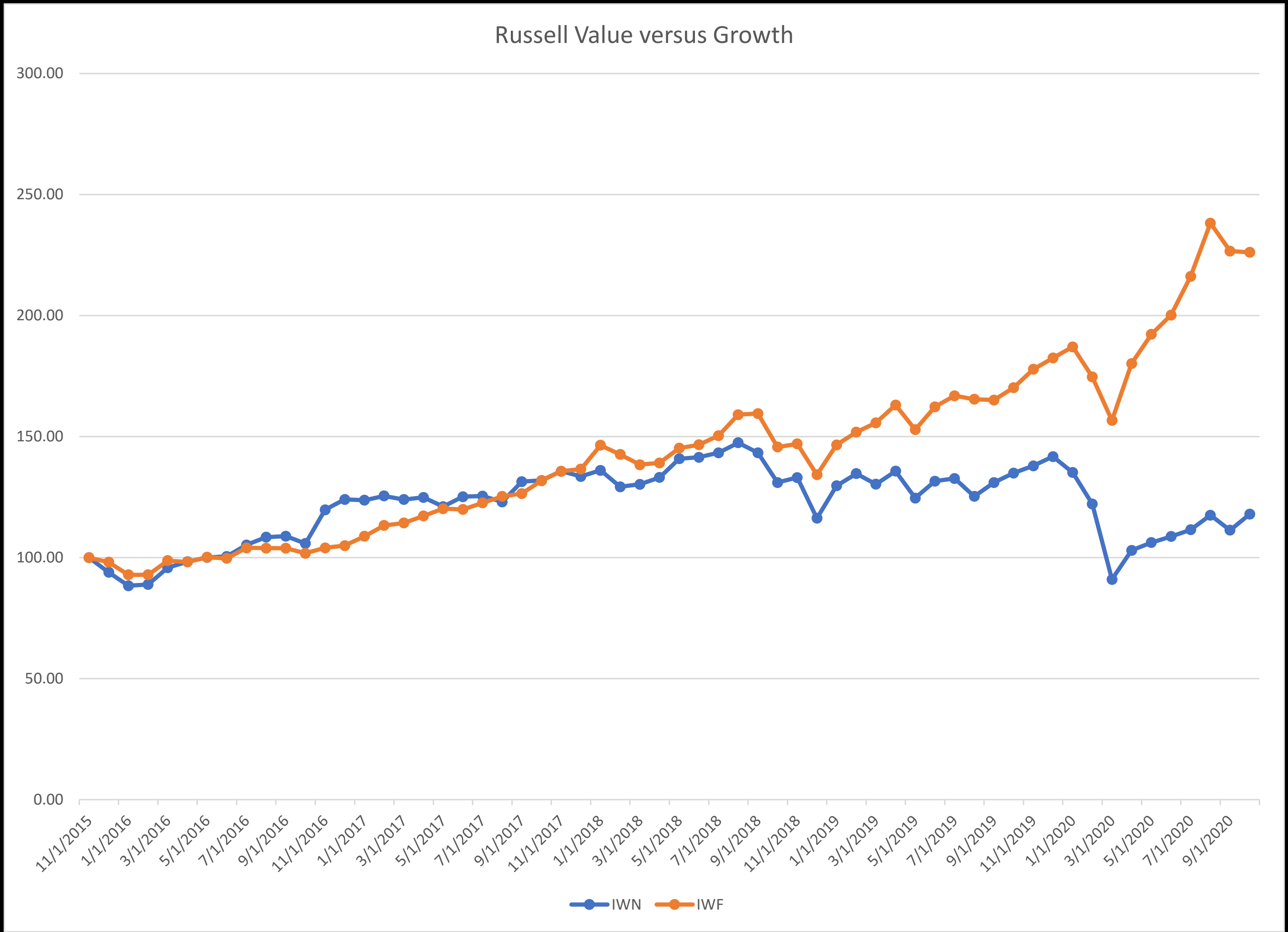
Bloomberg Ticker	Company	Market Cap (USD Bil)	Long-Term Performance	Percentage Sell-Side Analyst Buy Ratings	Aggressive Estimates with Implied Achievability	Adjusted Overweights by Active Managers	Institutional Trade Persistence	Current Overall Crowding Decile
SAP GR	SAP	189	3	3	4	1	5	1
ASML NA	ASML HLDG	153	1	6	3	1	5	1
DSY FP	DASSAULT SYSTEMES	48	3	8	3	1	4	1
ERICB SS	ERICSSON (LM) B	32	3	6	5	1	4	1
STM NQ	STMICROELECTRONICS	27	1	4	5	1	7	1
CAP FP	CAPGEMINI	22	4	6	4	1	4	1
WLN FP	WORLDLINE	16	2	2	4	1	1	1
WIX US	WIX.COM	13	1	2	6	1	2	1
LOGN SW	LOGITECH	13	1	8	5	1	3	1
NEXI IM	NEXI	12		8	1	1	3	1

2. New Observations on Crowding

Value and Size Getting Hammered



2. New Observations on Crowding
Russell Value versus Growth



108%
Difference

2. New Observations on Crowding
The Alpha of Strategies over Time

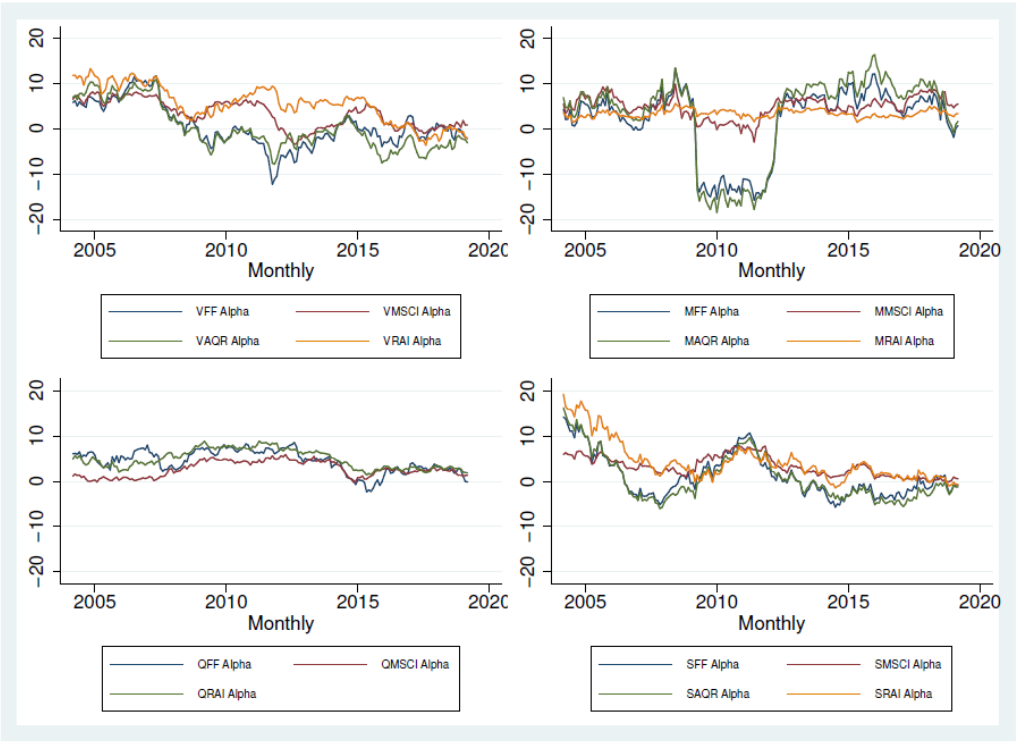


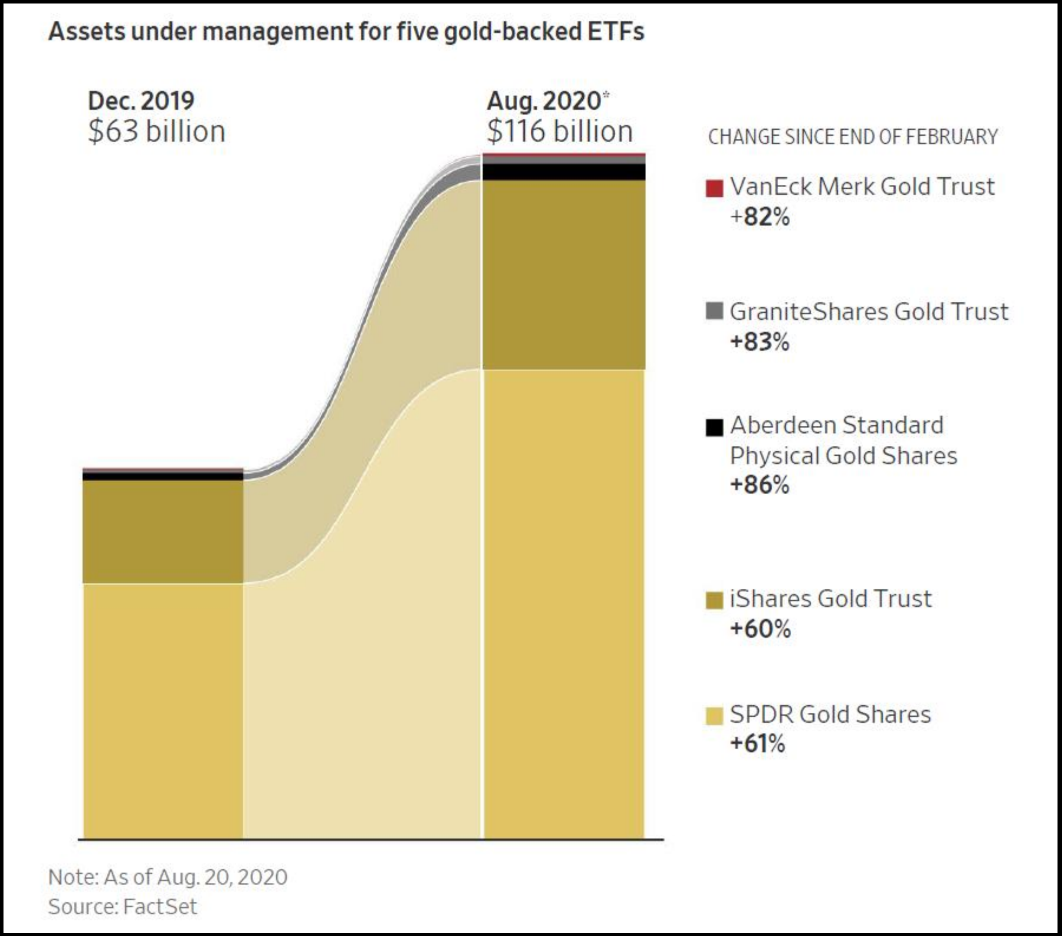
Figure 3: **Crowding and Factor Performance over Time** This figure the 3-year rolling alphas of various factors versus the S&P 500. Sample Period: April 2001 to December 2018.

- Value, Momentum, Quality and Size from 4 major sources.
- Alphas are generally declining … could it be crowding?

Source: Chincarini (unpublished work)

2. New Observations on Crowding

Gold being driven by AUM



2. New Observations on Crowding
New Investor Appetites

- **Investing Behavior Across Generations: Millennials, Gen X and Baby Boomers**
- As expected, the Baby Boomer generation ended the quarter with the largest balance $418,743, which was up from $367,425 last quarter. They were followed by Gen X at
- $231,798 and finally Millennials at $76,282. All balances were significantly up from last quarter.
- **All three generations had very similar equity holdings, with Apple, Amazon, Microsoft, Tesla, and Facebook coming in at the top**.

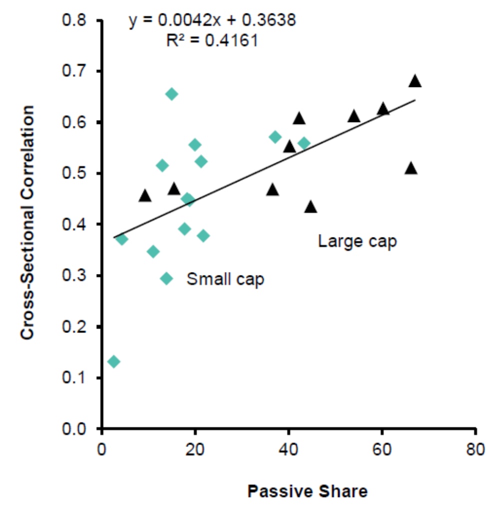
- Source: Charles Schwab, 06/30/20

3. Passive Crowding and Active Crowding

- Some worry that more money follows passive indexing could lead to crowding.

➢ For example, stocks become more correlated.

EXHIBIT 5: **... but higher passive share is associated with higher correlation spikes**

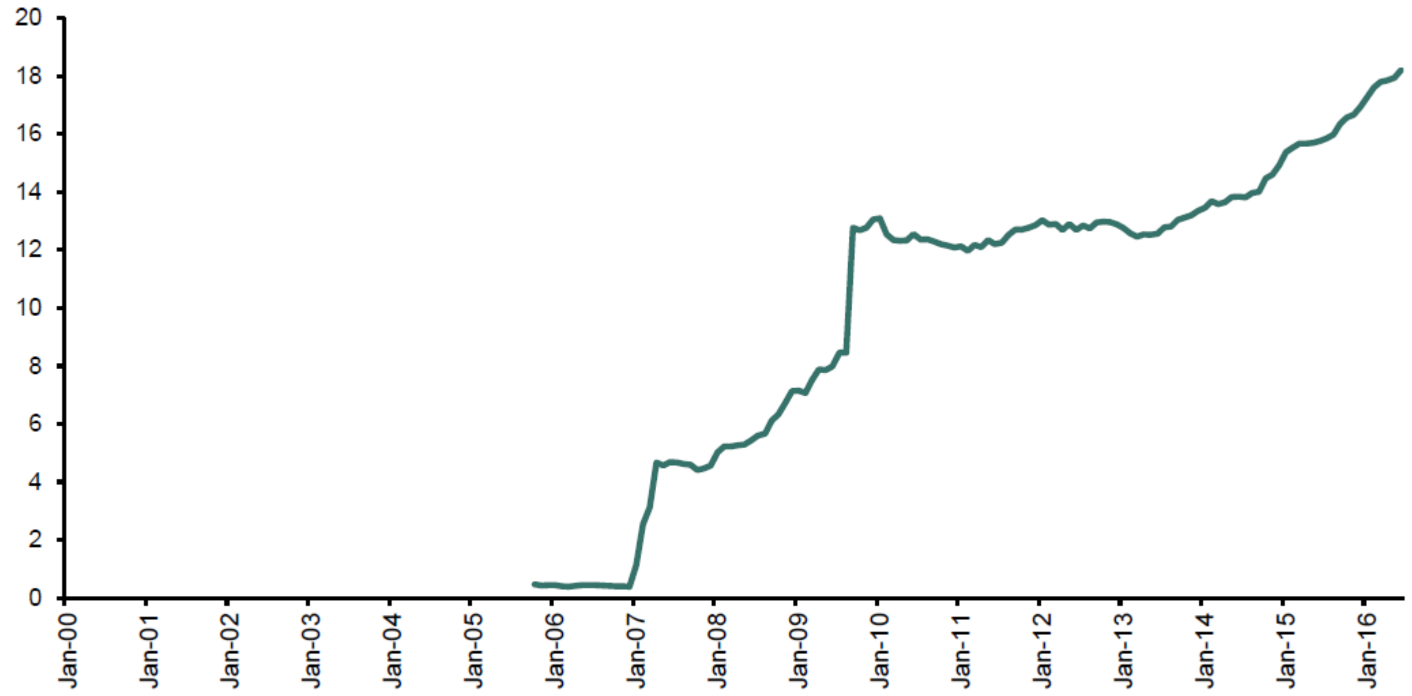


The scatter plot shows the peaks in cross-sectional correlation for US and Europe large and small cap styles in the periods (2003, 2007/08, 2009, 2010, 2011, 2015) against their respective level of passive share. To construct the large and small cap passive share series we adjusted the passive share of US and Europe broad market indices by the ratio of passive share for S&P 500 vs Russell 2000. Source: eVestment, EPFR, S&P, Russell, MSCI, Bernstein analysis

Source: Jenkins et al. Bernstein Report, August 23, 2016

3. Passive Crowding and Active Crowding

EXHIBIT 36: The growth of passive has been monotonic



Source: EPFR Global, Bernstein analysis

3. Passive Crowding and Active Crowding

- Obviously, more complicated – what is the real passive share? What about "passive" smart beta (rule-based)?

- Active managers can also crowd – is there crowding because of too few good ideas? Chasing similar good stuff (e.g. momentum)? Copycat ideas and small portfolios?

3. Passive Crowding and Active Crowding

- Let's create a simple world. M managers with a total of \$V(T) to invest in a total of n stocks. This represents entire world of investing.
- Each manager has \$V(i) of the \$V(T).
- Each manager chooses w(ij) for each stock j in his portfolio
- For simplicity, we assume passive managers invest equally weighted in each stock.
- Let's also assume there are n/2 good stocks and n/2 bad stocks in any period.
- **How should the active managers build their portfolios?**

3. Passive Crowding and Active Crowding

- Mean-Variance (tracking error) with respect to the passive benchmark?
- Pick only a fraction of stocks they think will have highest return?
- We are not modelling the effect on prices, but if too much flow alters prices and there is a saturation point, matters become more complex? For example, if only $V(max),j can go into stock j without it's expected return to be deteriorated, what should they do?
- Simultaneous action: Game theoretic move such that limit the amount of saturation/crowding in individual stocks

3. Passive Crowding and Active Crowding

- Predict Winners and Magnitude

- Simultaneous action: Game theoretic move such that limit the amount of saturation/crowding in individual stocks, but still pick highest expected return winners
- Sequential actions: Managers keep picking highest return stock until saturated, then next, and so on.

- Predict Winners but Not Magnitude

- Pick a diversified set of winners?
- Pick 50% of the stocks (get all winners)
- Use Mean-Variance with TE versus index

3. Passive Crowding and Active Crowding

- Is there another way to think about this?

- Selectivity Theory (Bolshakov and Chincarini (2020))

Chincarini, Ludwig (w/ Andrei Bolshakov). “Manager Skill and Portfolio Size with Respect to a Benchmark.” European Financial Management, February, 2020.

4a. The model

Assumption 1: In any given index, 50% of the stocks will outperform and 50% will underperform.

Assumption 2: Stock either outperforms or underperforms (1 or 0), magnitude is unimportant.

Assumption 3: A portfolio manager's constant skill lies in the probability to pick a "winner" versus a "loser".

Assumption 4: The benchmark and portfolio are equally-weighted.

4a. The model

We introduce the notion of omega (ω), where $\omega > 1$ if a portfolio manager is more likely to pick a good stock versus a bad stock.

To get a rough idea of how ω is related to probabilities, if $\omega = 1.1$ and a manager is picking the 1st stock, the probability of picking a good one is about 0.5238.

4a. The model

Two Possible Selection Methods for a group of n stocks out of a universe of N stocks.

Method 1: Bulk Selection

Method 2: Sequential Selection

4a. The model

Bulk Selection: This means that the portfolio manager selects the stocks into the portfolio ALL AT ONCE using his/her skill.

Mathematically, this is governed by the Fisher Noncentral Hypergeometric Distribution.

Sequential Selection: The portfolio manager decides ex-ante how many of the stocks in the benchmark to chose. Then he/she selects them ONE AT A TIME using his/her skill.

Mathematically, this is governed by the Wallenius Noncentral Hypergeometric Distribution

4a. The model

Simple Example: Benchmark has 10 stocks, 5 good, 5 bad. What's the probability of picking 3 good stocks in a portfolio of 5 stocks?

- **Bulk Selection** – no path dependency
- No skill (ω=1), then probability of getting 3 good: 39.68%
- Skill (ω=1.1), then probability of getting 3 good: 41.49%
- For 3: Numerator: $\binom{5}{3}\binom{5}{2}\omega^3$
- For 3: Denominator: $\binom{5}{0}\binom{5}{5}\omega^0+\binom{5}{1}\binom{5}{4}\omega^1+\binom{5}{2}\binom{5}{3}\omega^2+\binom{5}{3}\binom{5}{2}\omega^3+\binom{5}{4}\binom{5}{1}\omega^4+\binom{5}{5}\binom{5}{0}\omega^5$

4a. The model

Simple Example: Benchmark has 10 stocks, 5 good, 5 bad. What's the probability of picking more good stocks than bad stocks in a portfolio of 5 stocks?

- We need to sum up the probabilities of selecting 3, 4 and 5 stocks. The result is 53.4%

TABLE 1 A simple example of picking 5 stocks from the noncentral fisher distribution

This table shows a simple example of the noncentral Fisher distribution in the context of portfolio selection. The table shows the probability of selecting 0, 1, . . . , 5 good stocks in a portfolio of 5 stocks chosen from a 10-stock benchmark with an equal amount of good and bad stocks.

Number of Good Stocks	Numerator	Denominator	Probability of Event (%)
0	1.00	320.81	0.31
1	27.50	320.81	8.57
2	121.00	320.81	37.72
3	133.10	320.81	41.49
4	36.60	320.81	11.41
5	1.61	320.81	0.50

4a. The model

Simple Example: Benchmark has 10 stocks, 5 good, 5 bad. What's the probability of picking 3 good stocks in a portfolio of 5 stocks?

- **Sequential Selection** – path dependency, thus slightly more difficult calculation

- So once all combinations have been computed, you add them – in this case probability of 3 good stocks = 41.98%

- Similar steps for 4, 5 stocks to derive the probability of picking more good than bad stocks (54.39%).

TABLE 2 The different possible paths to picking 5 stocks

This table shows the different paths that can occur when selecting five stocks from a universe of 10 stocks. A ''1'' indicates that a good stock has been picked, while a ''0'' indicates a bad stock was picked. There are 10 possible combinations of picking five stocks consisting of three good stocks from a universe of 10 stocks containing an equal number of good and bad stocks. The probability of picking any given stock in the sequence is shown in the second section of the table, below the paths, and the probability of any individual sequence is shown at the bottom of the table.

Path 1	Path 2	Path 3	Path 4	Path 5	Path 6	Path 7	Path 8	Path 9	Path 10
1	1	1	0	0	0	1	0	1	1
1	0	1	1	1	0	0	1	1	0
1	1	0	1	0	1	1	1	0	0
0	1	1	1	1	1	0	0	0	1
0	0	0	0	1	1	1	1	1	1
Probabilities of Individual Picks									
52.38	52.38	52.38	47.62	47.62	47.62	52.38	47.62	52.38	52.38
46.81	53.19	46.81	57.89	57.89	42.11	53.19	57.89	46.81	53.19
39.76	52.38	60.24	52.38	47.62	64.71	52.38	52.38	60.24	47.62
69.44	45.21	45.21	45.21	59.46	59.46	54.79	54.79	54.79	59.46
64.52	64.52	64.52	64.52	52.38	52.38	52.38	52.38	52.38	52.38
Probabilities of Entire Sequence									
4.37	4.26	4.31	4.21	4.09	4.04	4.19	4.14	4.24	4.13

4a. The model

Portfolio Manager selects n stocks from a benchmark of N stocks. There are 50% "good" stocks and 50% "bad" stocks. Good stocks provide a 10% return and bad stocks a -10% return.

We will then compare a portfolio manager's performance against the benchmark via the Information Ratio.

When the portfolio manager draws from Fisher or Wallenius, we will know the expected number of good stocks. Thus, the expected return and standard deviation of the portfolio are given by:

$$E(r_{\mathrm{P}}) = p^* r_g + (1 - p^*) r_b,$$

$$S(r_{\mathrm{P}}) = (r_g - r_b) \frac{\sqrt{\sigma_x^2}}{n},$$

4a. The model

We can show that the Information Ratio of the portfolio will be:

$$IR(n/N, N, \omega, n_g, n_b) = \frac{E(r_P)}{S(r_P)}.$$

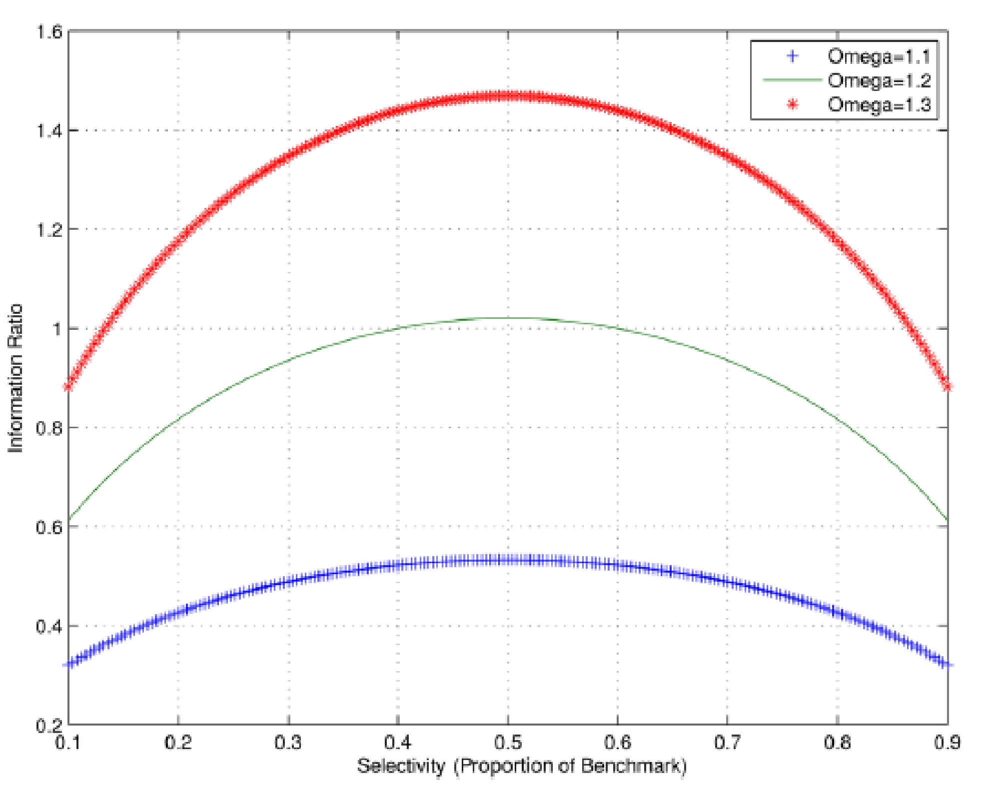
We also look at the Downside Information Ratio:

$$IR(n/N, N, \omega, n_g, n_b) = \frac{E(r_P) - E(r_{BM})}{SS(r_P - r_{BM})}$$

$$SS(r_P - r_{BM}) = \sqrt{\psi \sum_{i=1}^{n_l} \left[\min\left(0, r_{P,i} - r_{BM}\right)\right]^2 \cdot f(r_{P,i} - r_{BM})},$$

4b. Behavior of model

Example: N=500, n(g) = 250 n(b) = 250, ω=1.1 What is optimal selectivity ratio?

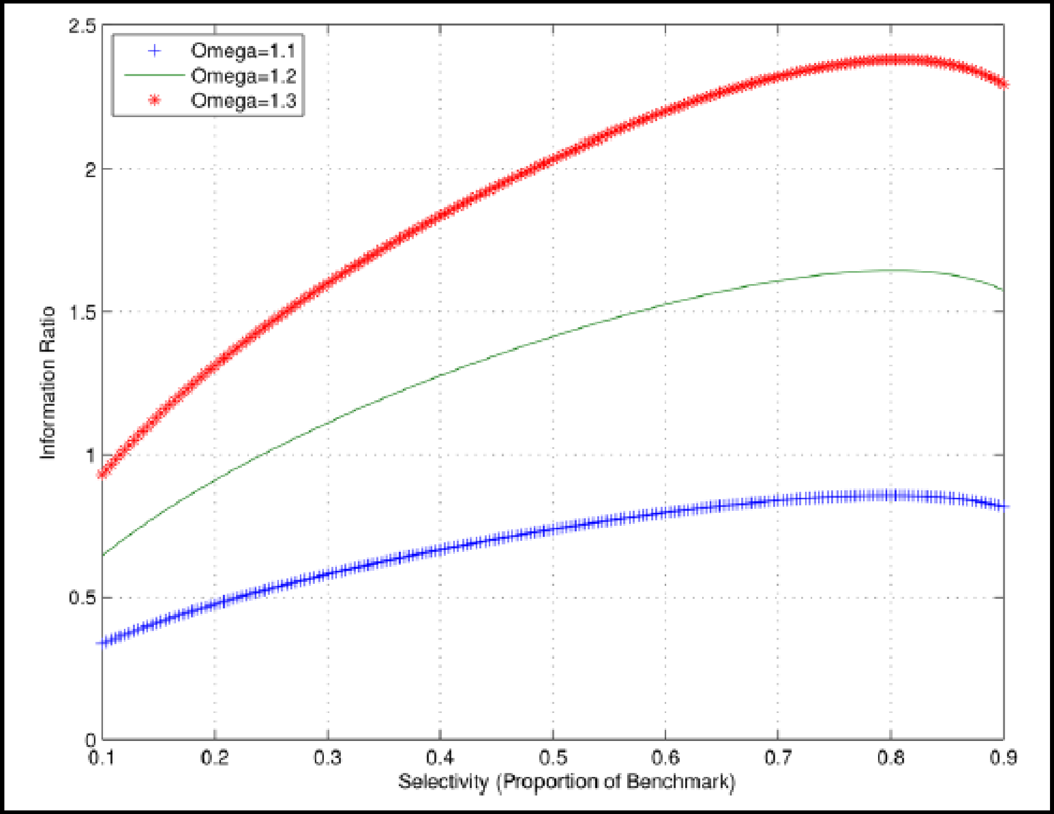


Bulk Selection = 50%

Note: For all ω, it's 50%!

4b. Behavior of model

Example: N=500, n(g) = 250 n(b) = 250, ω=1.1 What is optimal selectivity ratio?

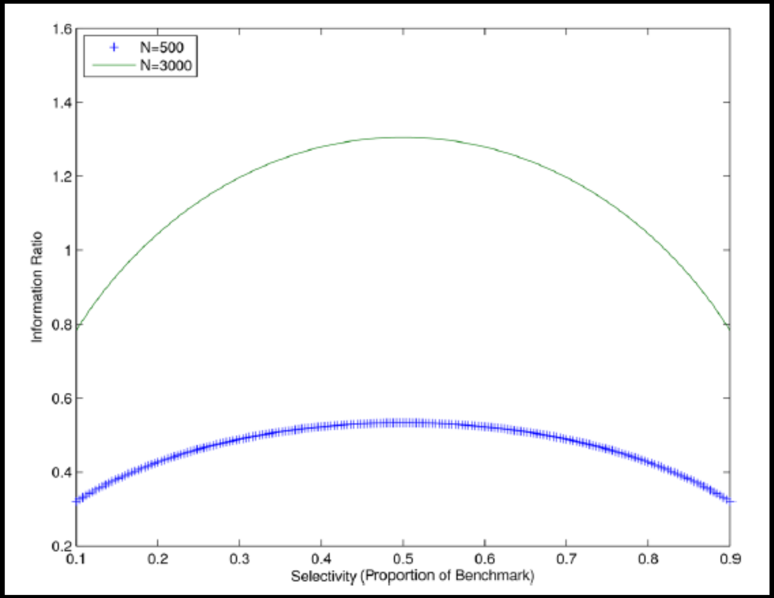


Sequential ~ 80%

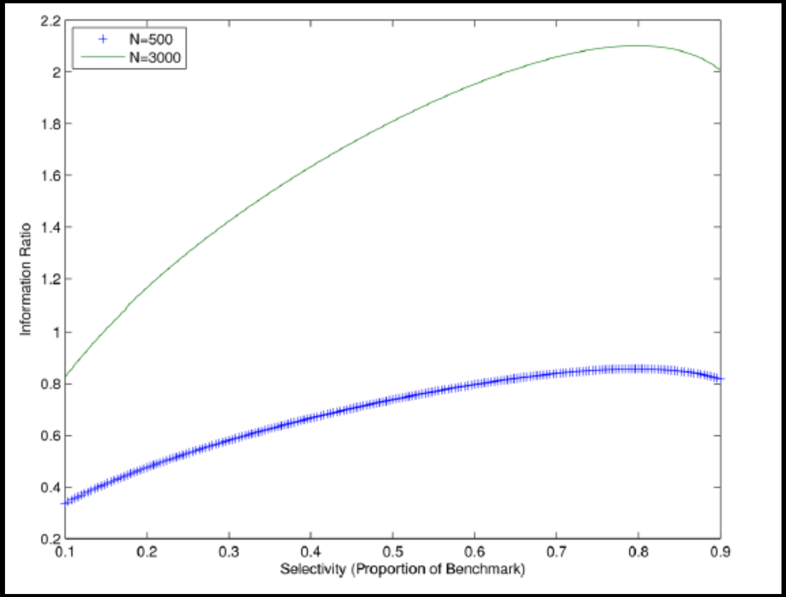
Note: For all ω, it's 80% (for reasonable values of ω)!

4b. Behavior of model

Question: How do more stocks in benchmark affect the result?



Same selectivity ratio, but higher IR.



4c. Characteristics of model

There are some general characteristics about the model's predictions.

Characteristic 1. Given a benchmark universe of stocks, N, the highest Information Ratio for a manager with skill level ω is obtained at a selectivity ratio (n/N) between 50% and 80%. For the bulk selection method, it is always at 50%. For the sequential selection method, it is near 80% for reasonable values of ω.

Characteristic 2. Given a manager with skill level ω that stays constant as the universe increases, a larger universe, M, will result in a larger Information Ratio, which is approximately $\sqrt{M/N}$ larger.

Characteristic 3. Given a certain selectivity ratio, the Information Ratio for the sequential selection method (Wallenius) will always be higher than the Information Ratio for the bulk selection (Fisher) method given a constant level of skill level, ω.

4d. The imperfection of IR

For most applications, the Information Ratio (IR) is thought to be a reliable measure of performance versus a benchmark.

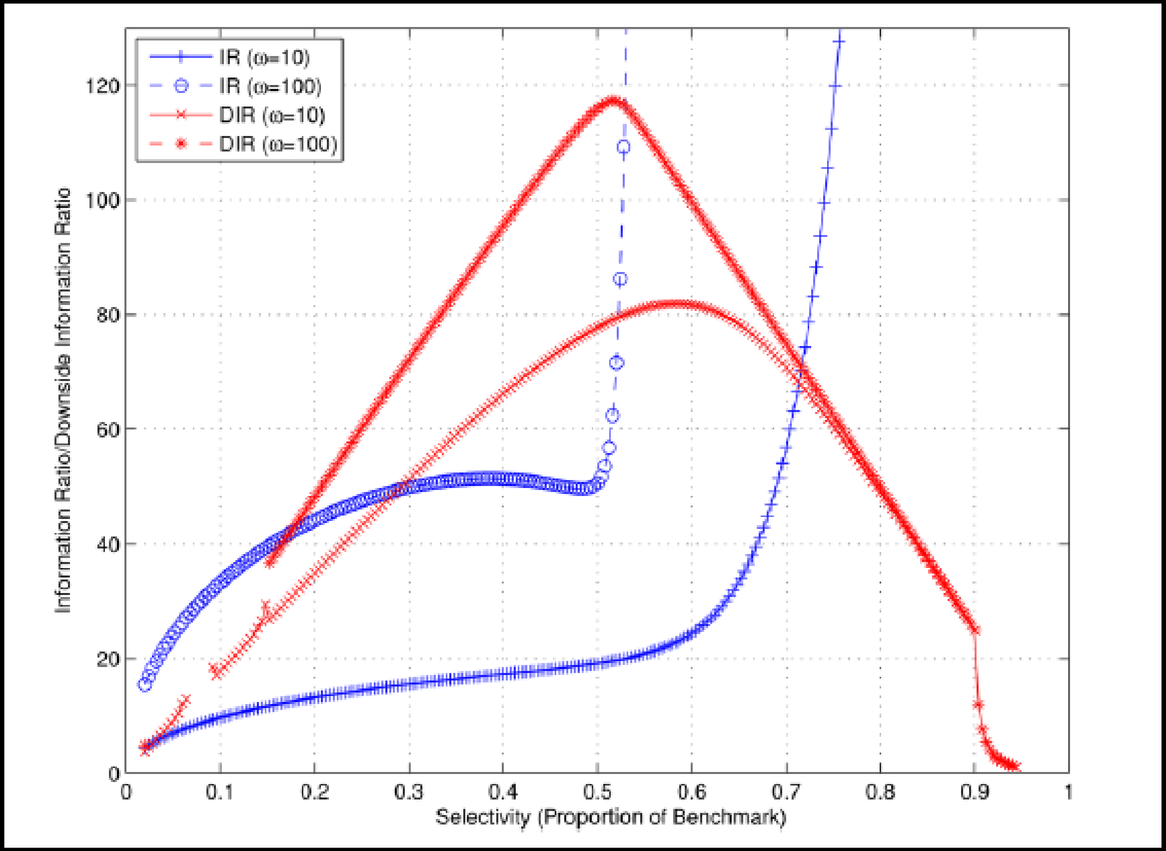
In our theoretical framework, when skill is very large, this measure performs very poorly.

For sequential picking, at very high levels of skill, the optimal IR is at 100% or complete indexing (TE declines faster than E(r)).

The problem is that at high levels of skill, although the probability of underperforming the benchmark is tiny, because the distribution of returns isn't centered around zero – IR is much less relevant, but DIR becomes appropriate criterion.

4d. The imperfection of IR

- However, the Downside Information Ratio (DIR) resolves this problem as can be seen in graph.



Bottom Line: With the more appropriate DIR, as skill goes to infinity, sequential chooses 50% of portfolio.

4e. Relaxing model assumptions

The model has certain simplifying assumptions about the investment universe.

Assumption 1: In any given index, 50% of the stocks will outperform and 50% will underperform.

Assumption 2: Stock either outperforms or underperforms (1 or 0), magnitude is unimportant.

Assumption 3: A portfolio manager's skill lies in the probability to pick a "winner" versus a "loser."

Assumption 4: The benchmark and portfolio are equally-weighted.

4e. Relaxing model assumptions

The results of the assumption relaxation are available on request in *Enhanced Indexing and Selectivity Theory* (Bolshakov, Chincarini, and Lewis) (2020) (email me). Here, I will just summarize.

One way to think of the results is in terms of the Information Ratio. IR = Excess Return / Tracking Error

4e. Relaxing model assumptions

Relax Assumption 1: Still near 80% Selectivity for Sequential
Relax Assumption 2: Still near 80% Selectivity for Sequential
Relax Assumption 4: Still above 70% Selectivity for Sequential

Why? In all cases, the average excess return doesn't really change, but the tracking error increases. But that doesn't change the optimal point much.

Relax Assumption 3 (more complicated): a. Steadily Decline = 50% (converges to Fisher (bulk). b. Jack Knife (skill for x% of universe) – changes to x% c. Ability Saturation (can only identify x% of good stocks, not all of them), close to 80% again d (unless super ability – high omega). Uncertainty in Skill (omega has a mean and vol), still close to 80%.

4e. Relaxing model assumptions

SUMMARY: Relaxing the simplifying assumptions required for the theory does not significantly alter its theoretical conclusion of which selectivity ratio maximizes the manager's Information Ratio for most of the assumptions.

5. Implications for Crowding in Active Management

- Since we have not modelled the pricing process of stocks, I continue with a rather simple example to give a flavor of the results.
- Suppose Psi of the dollars are active with omega>1 (selectivity theory), Beta are active managers omega=1 (random noise), and 1-Psi-Beta are the index/passive managers.
- Index managers will invest equally in each stock, uninformed active managers will equivalently so the same, since their picks are random.
- Active managers can do whatever they want, but for a moment, we will assume they are all the same, but can vary how many stocks they hold (selectivity), n(a).

5. Implications for Crowding in Active Management

- In this simple and incomplete model, relative crowding of active managers (i.e. with respect to passive and uninformed) is given by the following:

$$Crowding\ Active = \frac{\dfrac{\psi V^T}{n_a}}{\left[\dfrac{(1-\psi-\beta)V^T}{n} + \dfrac{\beta V^T}{n}\right]}$$

$$= \frac{\psi}{1-\psi}\frac{n}{n_a}$$

5. Implications for Crowding in Active Management

- With Psi=1, infinite active crowding.
- With Psi=0, infinite passive crowding

Assuming that 20% of the investment universe is run by active managers, then:

- With active at 10% selectivity (the usual), the crowding metric is 2.5.
- At 80% selectivity, the crowding metric is 0.3125 (much smaller)

8. FURTHER RESEARCH

- For crowding model, need to develop more and build a pricing function based on demand and supply – various paths to take.

- For Selectivity Theory, working on showing practical use with manager selection.

REFERENCES

1. Chincarini, Ludwig (w/ Andrei Bolshakov). "Manager Skill and Portfolio Size with Respect to a Benchmark." European Financial Management, February, 2020.

2. Bolshakov, Andrei, Chincarini, Ludwig B., and Lewis, Christopher. "Enhanced Indexing and Optimal Selectivity." Working Paper, 2020. Available upon request.

3. Chincarini, Ludwig B. and Daehwan Kim. *Quantitative Equity Portfolio Management*. New York, McGraw-Hill, 2006. *Note*: New Edition should be released in 2021 with lots of new stuff.

4. Chincarini, Ludwig B. *The Crisis of Crowding. Quant Copycats, Ugly Models, and the New Crash Normal*, Wiley, 2012.

Thank you

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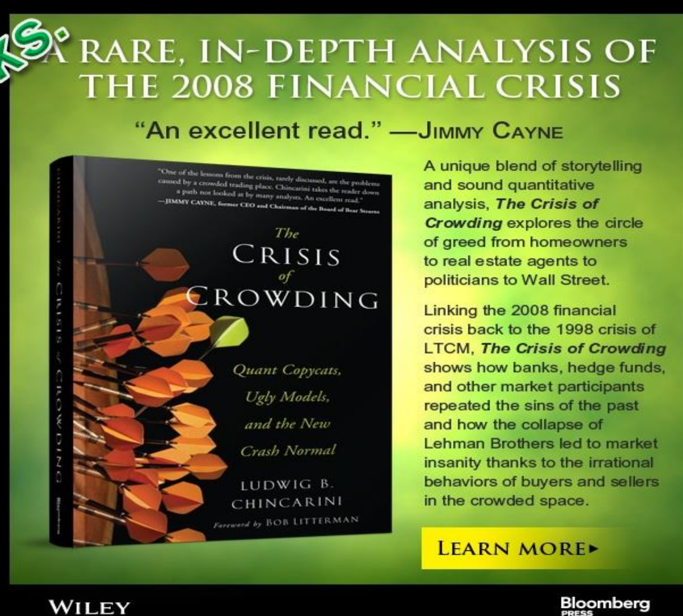
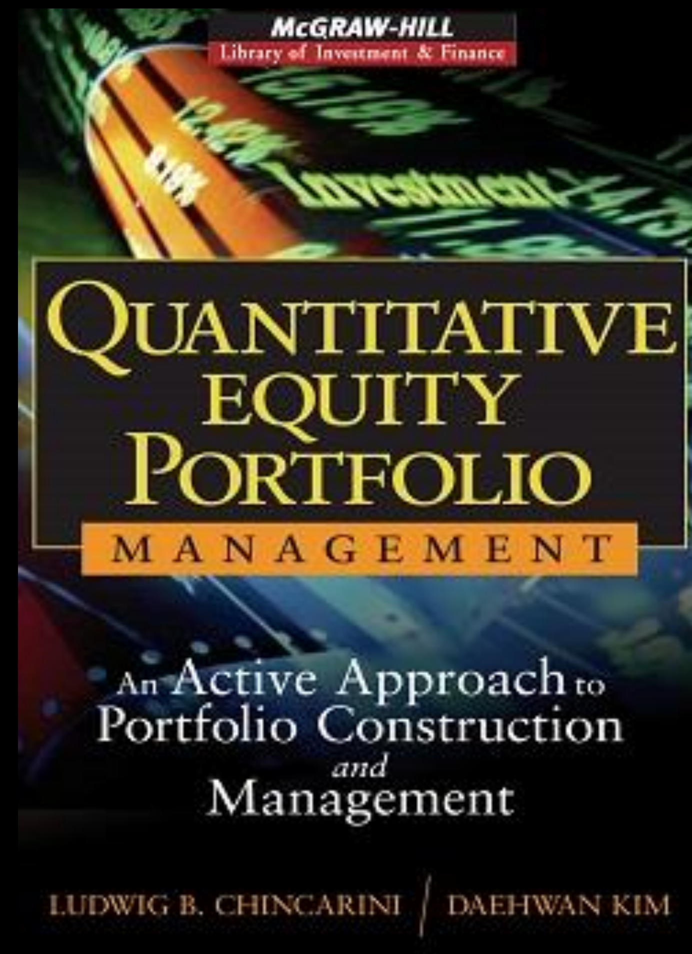
For more information on quantitative investing and crowding – buy the books:





Open Discussion for all Participants

1. Lots of research suggests holding fewer stocks for idiosyncratic alpha. How do you reconcile that with selectivity theory?
2. What happens to absolute return as selectivity increases?
3. What is your definition of crowding?
4. Isn't 80% getting close to passive investing?
5. When do you think value and growth will turnaround?

Appendix A: Recent New Research on Crowding

1. “Are Crowded Crowds Still Wise? Evidence from Financial Analysts' Geographic Diversity,” Gerken and Painter Working Paper, June 2020.

Examines when crowds can be damaging. Specifically, studies the behavior of analysts concentrated in one geographical region. They tend to infer too much from the local environment and behave similarly.

Appendix A: Recent New Research on Crowding

2. "Trade Less and Exit Overcrowded Markets. Lessons from International Mutual Funds," Dyakov, Jiang, Verbeek. Review of Finance, 2020.

Examines the capacity constraints (crowding) in active equity markets which have exploded (global AUM has grown from $29T in 2002 to $71 trillion in 2015). They define limits to aggregate active management. They find that a 1% increase in active funds versus the entire US equity market leads to a decline in 14 bps per month performance.

My discussion of their paper before published:
https://onh.ccd.myftpupload.com/pres/Discussion_Crowding_MFs_2019.pdf

Appendix A: Recent New Research on Crowding

5. "Currency Crowdedness Generated by Global Bond Funds," Konstantinov, Geuorgui, Journal of Portfolio Management, Winter 2017. *Note*: Older paper, but I only recently learned about it.

Examines the potential crowding of global fund managers due to their currency-related strategies. The author finds that global funds are crowded using style analysis exposure to various currency factors, such as the global carry, value, FX vol, and trend factors.

6. "The Mismatch Between Mutual Fund Scale and Skill," Song, Yang. Journal of Finance, October 2020.

Examines mutual fund exposures to common factors and asset flows. Finds that funds with prior factor related returns receive large uninformed flows and these "crowded" styles have subsequent poor returns.

Appendix A: Recent New Research on Crowding

3. “What alleviates Crowding in Factor Investing,” DiMiguel, Martin-Utrera, and Uppal, Working Paper, January, 2020.

Examines the issue of crowding amongst smart beta funds. The authors find (quite intuitive) that if managers have several unrelated smart beta strategies and trade them at the same time, they can reduce market impact costs that damage any specific smart beta strategy. Also, mentions the tradeoff between competition in smart beta and crowding. *Note (LBC)*: Does not reduce the danger of exogenous shock in a particular crowded strategy causing dislocation.

Appendix A: Recent New Research on Crowding

4. "Crowding: Evidence from Fund Managerial Structure," Harvey, Liu, Tan, and Zhu. Working Paper, March 2020.

Examines the trend in fund management from 30% teams to 70% teams in last 30 years. They argue that it's a direct result of crowding. That, as AUM grew, teams needed to form so that there was a diversification of ideas and investments. That is, to eliminate the crowding of ideas. The authors attempt to show that this is true with several statistical tests.

Appendix A: Recent New Research on Crowding

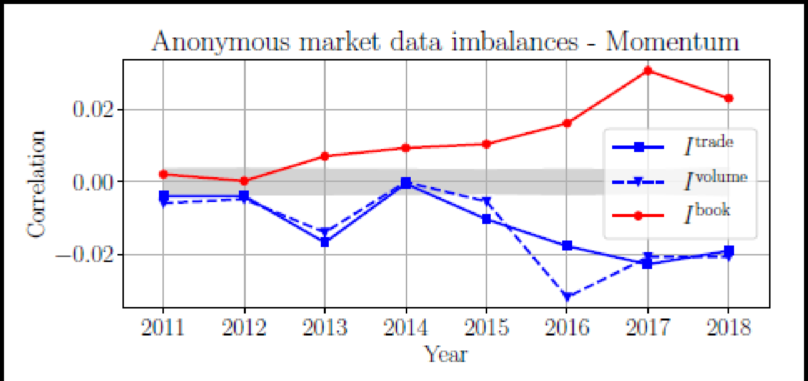
7. "Optimal Disclosure in Crowded Markets," Kim, Taejin and Vishal Mangla, Working Paper, November 2018. *Note*: Also an older paper, but just recently became aware of it.

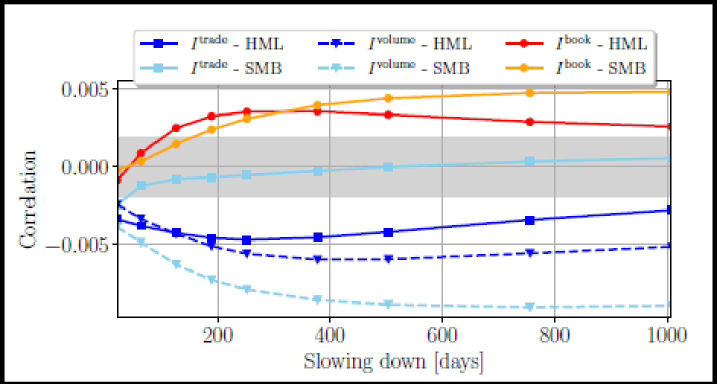
Examines whether a regulator that observes the crowding can alleviate the problems from a liquidity shock to a crowded space. They find that announcements done randomly (not all the time) about crowding can reduce the harmful effects of crowding.

Appendix A: Recent New Research on Crowding

8. "Zooming in on Equity Factor Crowding," Volpati, Benzaquen, Eisler, Mastromatteo, Toth, and Bouchaud, Working Paper, January 20, 2020.

Examines the trading imbalance or pressure as a results of common factor strategies. They find that momentum and value strategies are crowded and have positive correlation with trade imbalance measures and this correlation has increased over time.





Appendix B: Older Academic References on Crowding

A. "The Failure of LTCM," Chincarini (1998)
B. "Sophisticated Investors and Market Strategy," Stein (2009)
C. *The Crisis of Crowding*, Chincarini (2012)
D. "The Externalities of Crowded Trades," Blocher (2013)
E. "Standing out from the Crowd. Measuring Crowding in Quantitative Strategies," Cahan and Luo (2013)
F. "Stock portfolio structure of individual investors infers future trading behavior," Bohlin and Rosvall (2014)

Appendix B: Older Academic References on Crowding

G. "Dimensions of Popularity," Ibbotson and Idsorek (2014)).

H. "Crowded Trades: An Overlooked Systemic Risk for Central Clearing Counterparties," Menkveld (2014)

I. "The Effects of Short Sales and Leverage Constraints on Market Efficiency," Yan (2014).

J. "Omitted Risks or Crowded Strategies: Why Mutual Fund Comovement Predicts Future Performance," Chue (2015).

K. "Fire, Fire. Is Low Volatility a Crowded Trade," Marmar (2015)

L. "Days to Cover and Short Interest," Hong et al. (2015)

Appendix B: Older Academic References on Crowding

M. “Portfolio Construction and Crowding” Bruno, Chincarini, Davis, and Ohara (2018).

N. “Transaction Costs and Crowding” Chincarini (2017)

O. “Mutual Fund Crowding and Stock Returns,” Zhong et al. (2016)

P. “Hedge fund crowds and mispricing,” Sias et al. (2016)

R. “Individual stock Crowded Trades, Individual Stock Investor Sentiment, and Excess Returns,” Yang and Zhou (2016)

Appendix B: Older Academic References on Crowding

S. "The Impact of Pensions and Insurance on Global Yield Curves", Greenwood and Vissing-Jorgenson (2018)

T. "Institutional Selling of Stocks with Illiquidity Shock", Krystaniak (2016)

U. "Arbitrage Crowdedness and Portfolio Momentum," Chen (2018)

V. "Copycatting and Public Disclosure: Direct Evidence from Peer Companies' Digital Footprints," Cao et al. (2018).

W. "Crowded Trades and Tail Risk," Brown et al (2019)

Appendix B: Older Academic References on Crowding

X. "Granularity and Downside Risk in Equity Markets," Ghysels et al (2018)

Y. "The Impact of Crowding in Alternative Risk Premia Investing," Baltas (2019)

Z. "Mutual Fund Herding after 13-D Filings," (Agapova and Rodriguez (2019))

AA. "Optimal Timing and Tilting of Equity Factors," Dicthl et al. (2019)

BB. Systematic Investment Strategies (Giamourdis (2017))

CC. Trading in Crowded Markets (Gorban et al. (2018))

Appendix B: Older Academic References on Crowding

DD. "Institutional Consensus: Information or Crowding?" Klein et al. (2019)

EE. "Stochastic investor sentiment, crowdedness and deviation of asset prices from fundamentals," Zhou and Yang (2019)

FF. "Modelling Transaction Costs when Trades May Be Crowded: A Bayesian Network Using Partially Observable Orders Imbalance," Briere et al. (2019)

GG. "Everybody's Doing It: Short Volatility Strategies and Shadow Financial Insurers," Bhansali and Harris (2018)